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OSN Model For Business Growth Using Ecommerce Product Recommendation

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Abstract: **Now A Days Online Shopping Has Achieved A Tremendous Popularity Within Very Less Amount Of Time. Recently Few Ecommerce Websites Has Been Developed Their Functionalities To A Extent Such That They Recommend The Product For Their Users Referring To The Connectivity Of The Users To The Social Media And Provide Direct Login From Such Social Media Such As Facebook, Twitter, Whatsapp. Recommend The Users That Are Totally New To The Website Client Novel Solution For Cross-Site Cold-Start Product Recommendation That Aims For Recommending Products From E-Commerce Websites. In Specific Propose Learning Both Users And Products Feature Representations From Data Collected From E-Commerce Websites Using Recurrent Top-K To Transform User's Social Networking Features Into User Embeddings. The Survey Paper Develops A Top-K Approach Which Can Manipulate The Learnt User Implanting For Cold-Start Product Recommendation.**

Keywords: **Online Social Networking; Facebook;**

INTRODUCTION

Data Mining Is A Process Of Extracting Interesting Knowledge Or Patterns From Large Databases. There Are Several Techniques That Have Been Used To Discover Such Kind Of Knowledge, Most Of Them Resulting From Machine Learning And Statistics. The Greater Part Of These Approaches Focus On The Discovery Of Accurate Knowledge. Though This Knowledge May Be Useless If It Does Not Offer Some Kind Of Surprisingness To The End User. The Tasks Performed In The Data Mining Depend On What Sort Of Knowledge Someone Needs To Mine. E-Commerce And Social Networking Have Become Increasingly Blurred. E-Commerce Websites Such As Ebay Features Many Of The Characteristics Of Social Networks, Including Real-Time Status Updates And Interactions Between Its Buyers And Sellers. Some E-Commerce Websites Also Support The Mechanism Of Social Login, Which Allows New Users To Sign In With Their Existing Login Information From Social Networking Services Such As Facebook, Twitter Or Google+. Both Facebook And Twitter Have Introduced A New Feature Last Year That Allow Users To Buy Products Directly From Their Websites By Clicking A "Buy" Button To Purchase Items In Adverts Or Other Posts. Product Recommendation Is A Key Area To Focus For Increased Sales For Any E-Commerce Website. There Are Many Algorithms Which Focus On Connecting The Social Media To E-Commerce But None Are Focused On Product Recommendation By Leveraging The Social Media Information Like Demographic, Micro-Blogs, Location Etc.

RELATED WORK

1) J. Wang And Y. Zhang, Opportunity Model For E-Commerce Recommendation: Right Product; Right Time - Most Of Existing E-Commerce Recommender Systems Aim To Recommend The Right Product To A User, Based On Whether The User Is Likely To Purchase Or Like A Product. On The Other Hand, The Effectiveness Of Recommendations Also Depends On The Time Of The Recommendation. Let Us Take A User Who Just Purchased A Laptop As An Example. She May Purchase A Replacement Battery In 2 Years (Assuming That The Laptop's Original Battery Often Fails To Work Around That Time) And Purchase A New Laptop In Another 2 Years. In This Case, It Is Not A Good Idea To Recommend A New Laptop Or A Replacement Battery Right After The User Purchased The New Laptop. It Could Hurt The User's Satisfaction Of The Recommender System If She Receives A Potentially Right Product Recommendation At The Wrong Time. We Argue That A System Should Not Only Recommend The Most Relevant Item, But Also Recommend At The Right Time. This Paper Studies The New Problem: How To Recommend The Right Product At The Right Time? We Adapt The Proportional Hazards Modeling Approach In Survival Analysis To The Recommendation Research Field And Propose A New Opportunity Model To Explicitly Incorporate Time In An Ecommerce Recommender System. The New Model Estimates The Joint Probability Of A User Making A Follow-Up Purchase Of A Particular Product At A Particular Time. This Joint Purchase Probability Can Be Leveraged By Recommender Systems In Various Scenarios, Including The Zero-Query Pullbased Recommendation Scenario (E.G. Recommendation

On An Ecommerce Web Site) And A Proactive Push-Based Promotion Scenario (E.G. Email Or Text Message Based Marketing). We Evaluate The Opportunity Modeling Approach With Multiple Metrics. Experimental Results On A Data Collected By A Realworld E-Commerce Website(Shop.Com) Show That It Can Predict A User's Follow-Up Purchase Behavior At A Particular Time With Descent Accuracy. In Addition, The Opportunity Model Significantly Improves The Conversion Rate In Pull-Based Systems And The User Satisfaction/Utility In Push-Based Systems [1]. 2) M. Giering, Retail Sales Prediction And Item Recommendations Using Customer Demographics At Store Level -: This Paper Outlines A Retail Sales Prediction And Product Recommendation System That Was Implemented For A Chain Of Retail Stores. The Relative Importance Of Consumer Demographic Characteristics For Accurately Modeling The Sales Of Each Customer Type Are Derived And Implemented In The Model. Data Consisted Of Daily Sales Information For 600 Products At The Store Level, Broken Out Over A Set Of Non-Overlapping Customer Types. A Recommender System Was Built Based On A Fast Online Thin Singular Value Decomposition. It Is Shown That Modeling Data At A Finer Level Of Detail By Clustering Across Customer Types And Demographics Yields Improved Performance Compared To A Single Aggregate Model Built For The Entire Dataset. Details Of The System Implementation Are Described And Practical Issues That Arise In Such Real-World Applications Are Discussed. Preliminary Results From Test Stores Over A One-Year Period Indicate That The System Resulted In Significantly Increased Sales And Improved Efficiencies. A Brief Overview Of How The Primary Methods Discussed Here Were Extended To A Much Larger Data Set Is Given To Confirm And Illustrate The Scalability Of This Approach [2]. 3) G. Linden, B. Smith, And J. York, Amazon.Com Recommendations: Item-To-Item Collaborative Filtering - Recommendation Algorithms Are Best Known For Their Use On E-Commerce Web Sites, Where They Use Input About A Customer's Interests To Generate A List Of Recommended Items. Many Applications Use Only The Items That Customers Purchase And Explicitly Rate To Represent Their Interests, But They Can Also Use Other Attributes, Including Items Viewed, Demographic Data, Subject Interests, And Favorite Artists. At Amazon.Com, We Use Recommendation Algorithms To Personalize The Online Store For Each Customer. The Store Radically Changes Based On Customer Interests, Showing Programming Titles To A Software Engineer And Baby Toys To A New Mother. There Are Three Common Approaches To Solving The Recommendation Problem: Traditional Collaborative Filtering, Cluster Models, And Search-Based Methods. Here, We Compare These Methods With Our Algorithm, Which We Call Item-To-Item Collaborative Filtering. Unlike Traditional Collaborative Filtering, Our Algorithm's Online Computation Scales Independently Of The Number Of Customers And Number Of Items In The Product Catalog. Our Algorithm Produces Recommendations In Real-Time, Scales To Massive Data Sets, And Generates High Quality Recommendations [3].

CONTENT-BASED FILTERING

Information Filtering Systems Are Designed To Classify A Stream Of Dynamically Generated Information Dispatched Asynchronously By An Information Producer And Present To The User Those Information That Are Likely To Satisfy His/Her Requirements [3]. In Content-Based Filtering Each User Is Assumed To Operate Independently. As A Result, A Content-Based Filtering System Selects Information Items Based On The Correlation Between The Content Of The Items And The User Preferences As Opposed To A Collaborative Filtering System That Chooses Items Based On The Correlation Between People With Similar Preferences [4]. While Electronic Mail Was The Original Domain Of Early Work On Information Filtering, Subsequent Papers Have Addressed Diversified Domains Including Newswire Articles, Internet "News" Articles, And Broader Network Resources [5], [6]. Documents Processed In Content-Based Filtering Are Mostly Textual In Nature And This Makes Content-Based Filtering Close To Text Classification. The Activity Of Filtering Can Be Modeled, In Fact, As A Case Of Single Label, Binary Classification, Partitioning Incoming Documents Into Relevant And Non Relevant Categories [7]. More Complex Filtering Systems Include Multi-Label Text Categorization Automatically Labeling Messages Into Partial Thematic Categories. In [4] A Detailed Comparison Analysis Has Been Conducted Confirming Superiority Of Boosting-Based Classifiers [10], Neural Networks [11] And Support Vector Machines [12] Over Other Popular Methods, Such As Rocchio And Naive Bayesian. However, It Is Worth To Note That Most Of The Work Related To Text Filtering By ML Has Been Applied For Long-Form Text And The Assessed Performance Of The Text Classification Methods Strictly Depends On The Nature Of Textual Documents.

POLICY-BASED PERSONALIZATION OF OSN CONTENTS

There Have Been Some Proposals Exploiting Classification Mechanisms For Personalizing Access In Osns. For Instance, In [8] A Classification Method Has Been Proposed To Categorize Short Text Messages In Order To Avoid

Overwhelming Users Of Microblogging Services By Raw Data. The User Can Then View Only Certain Types Of Tweets Based On His/Her Interests. In Contrast, Golbeck And Kuter [9] Propose An Application, Called Filmtrust, That Exploits OSN Trust Relationships And Provenance Information To Personalize Access To The Website. However, Such Systems Do Not Provide A Filtering Policy Layer By Which The User Can Exploit The Result Of The Classification Process To Decide How And To Which Extent Filtering Out Unwanted Information. In Contrast, Our Filtering Policy Language Allows The Setting Of Frs According To A Variety Of Criteria, That Do Not Consider Only The Results Of The Classification Process But Also The Relationships Of The Wall Owner With Other OSN Users As Well As Information On The User Profile. Moreover, Our System Is Complemented By A Flexible Mechanism For BL Management That Provides A Further Opportunity Of Customization To The Filtering Procedure. The Approach Adopted By Mywot Is Quite Different. In Particular, It Supports Filtering Criteria Which Are Far Less Flexible Than The Ones Of Filtered Wall. Content Filtering Can Be Considered As An Extension Of Access Control, Since It Can Be Used Both To Protect Objects From Unauthorized Subjects, And Subjects From Inappropriate Objects. In The Field Of Osns, The Majority Of Access Control Models Proposed So Far Enforce Topology-Based Access Control, According To Which Access Control Requirements Are Expressed In Terms Of Relationships That The Requester Should Have With The Resource Owner. We Use A Similar Idea To Identify The Users To Which A FR Applies. However, Our Filtering Policy Language Extends The Languages Proposed For Access Control Policy Specification In Osns To Cope With The Extended Requirements Of The Filtering Domain. Indeed, Since We Are Dealing With Filtering Of Unwanted Contents Rather Than With Access Control, One Of The Key Ingredients Of Our System Is The Availability Of A Description For The Message Contents To Be Exploited By The Filtering Mechanism. In Contrast, No One Of The Access Control Models Previously Cited Exploit The Content Of The Resources To Enforce Access Control. Moreover, The Notion Of Bls And Their Management Are Not Considered By Any Of The Above-Mentioned Access Control Models. Finally, Our Policy Language Has Some Relationships With The Policy Frameworks That Have Been So Far Proposed To Support The Specification And Enforcement Of Policies Expressed In Terms Of Constraints On The Machine Understandable Resource Descriptions Provided By Semantic Web Languages. Examples Of Such Frameworks Are Kaos And REI, Focusing Mainly On Access Control, Protune [13], Which Provides Support Also To Trust Negotiation And Privacy Policies, And WIQA [14], Which Gives End Users The Ability Of Using Filtering Policies In Order To Denote Given ”Quality” Requirements That Web Resources Must Satisfy To Be Displayed To The Users. However, Although Such Frameworks Are Very Powerful And General Enough To Be Customized And/Or Extended For Different Application Scenarios They Have Not Been Specifically Conceived To Address Information Filtering In Osns And Therefore To Consider The User Social Graph In The Policy Specification Process.

PROPOSED METHODOLOGY

OSN System Construction Module: In The First Module, We Develop The Online Social Networking (OSN) System Module. We Erect The System With The Feature Of Online Social Networking. Where, This Module Is Used For New User Registrations And After Registrations The Users Can Login With Their Authentication. Where After The Existing Users Can Send Messages To Privately And Publicly, Options Are Built. Users Can Also Share Post With Others. The User Can Able To Search The Public Posts And Other User Profiles. In This Module Users Can Also Send And Accept Friend Requests. With All The Basic Feature Of Online Social Networking System Modules Is Build Up In The Initial Module, To Prove And Evaluate Our System Features. Given An E-Commerce Website, With A Set Of Its Users, A Set Of Products And Purchase Record Matrix, Each Entry Of Which Is A Binary Value Representing Whether Has Purchased Product. Each User Is Associated With A Set Of Purchased Products With The Purchase Timestamps. Furthermore, A Small Subset Of Users Can Be Linked To Their Microblogging Accounts (Or Other Social Network Accounts).

Microblogging Feature Selection : In This Module, We Develop The Microblogging Feature Selection. Prepare A List Of Potentially Useful Microblogging Attributes And Construct The Microblogging Feature Vector For Each Linked User. Generate Disperture Feature Representations Using The Information From All The Users On The Ecommerce Website Through Deep Learning. Learn The Mapping Function, Which Transforms The Microblogging Attribute Information Au To The Distributed Feature Representations In The Second Step. It Utilizes The Feature Representation Pairs Of All The Linked Users As Training Data. A Demographic Profile (Often Shortened As “A Demographic”) Of A User Such As Gender, Age And Education Can Be Used By Ecommerce Companies To Provide Better Personalized Services. We Extract Users’ Demographic Attributes From Their Public Profiles.

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Demographic Attributes Have Been Shown To Be Very Important In Marketing, Especially In Product Acceptance For Consumers.

Learning Product Embedding: In The Previous Module, We Develop The Feature Selection, But It Is Not Straightforward To Establish Connections Between Users And Products.

Instinctively, Products And Users Should Be Represented In The Same Feature Space So That A User Is Closer To The Products That He/She Has Purchased Compared To Those He/She Has Not. Inspired By The Recently Proposed Methods In Learning Word Embeddings, We Propose To Learn User Embeddings Or Distributed Representation Of User In A Similar Way. Given A Set Of Symbol Sequences, A Fixed-Length Vector Representation For Each Symbol Can Be Learned In A Latent Space By Exploiting The Background Information Among Symbols, In Which "Similar" Symbols Will Be Mapped To Nearby Positions. If We Treat Each Product ID As A Word Token, And Convert The Historical Purchase Records Of A User Into A Time Stamped Sequence, We Can Then Use The Same Methods To Learn Product Embeddings. Unlike Matrix Factorization, The Order Of Chronological Purchases From A User Can Be Naturally Captured.

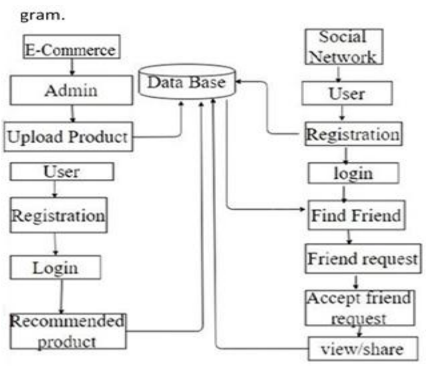

Fig. Proposed Methodology

Cold-Start Product Recommendation: We Used A Local Host Based E-Commerce Dataset, Which Contains Some User Transaction Records. Each Transaction Record Consists Of A User ID, A Product ID And The Purchase Timestamp. We First Group Transaction Records By User Ids And Then Obtain A List Of Purchased Products For Each User. For Our Methods, An Important Component Is The Embedding Models, Which Can Be Set To Two Simple Architectures, Namely CBOW And Skip-

From The Social Networking Site. E-Commerce Login Add The Products To The Database. Using The Demographic Attributes Such As Gender, Interests, Age Related Product Was Selected Automatically From The Database.

EXPERIMENTAL EVALUATION

Most Research Handiest Consciousness On Constructing Solutions Inside Sure E-Commerce Web Sites And Specifically Utilize Users' Ancient Transaction Data. To The Satisfactory Of Our Expertise, Pass-Site Cold-Begin Product Advice Has Been Rarely Studied Before. There Has Also Been A Huge Body Of Research Paintings Focusing Mainly At The Cold-Begin Advice Hassle. Seroussi Et Al. Proposed To Make Use Of The Data From Customers' Public Profiles And Subjects Extracted From User Generated Content Material Right Into A Matrix Factorization Model For New Users' Rating Prediction. Zhang Et Al. Recommend A Semi-Supervised Ensemble Getting To Know Algorithm. Schein Proposed A Method By Way Of Combining Content And Collaborative Records Beneath A Unmarried Probabilistic Framework. Lin Et Al. Addressed The Bloodlessbegin Problem For App Advice .

They Only Awareness On Insignia Or Class-Degree Purchase Desire Based On A Skilled Classifier, Which Cannot Be At Once Carried Out To Our Go-Website Online Bloodless Begin Product Advice Assignment. Their Features Only Consist Of Gender, Age And Facebook Likes, As Opposed To A Wide Range Of Capabilities Explored In Our Approach. They Do Now Not Don't Forget How To Transfer Varied Statistics From Social Media Web Sites Into A Form That Is Prepared For Use On The E-Trade Facet, That Is The Key To Address The Cross-Web Page Bloodless-Begin Recommendation Problem.

We Take A Look At An Thrilling Hassle Of Recommending Merchandise From E-Commerce Websites To Users At Social Networking Web Sites Who Do Now Not Have Ancient Purchase Data, I.E., In "Cold-Start" Conditions. We Called This Hassle Move-Web Site Cold-Begin Product Recommendation. In Our Hassle Putting Here, Simplest The Customers' Social Networking Facts Is Available And It Is A Difficult Task To Transform The Social Networking Statistics Into Latent Person Capabilities Which Can Be Effectively Used For Product Recommendation. To Deal With This Business Enterprise, We Advise To Use The Linked Customers Across Social Networking Sites And E-Commerce Web Sites (Users Who've Social Networking Accounts And Have Made Purchases On E-Commerce Web Sites) As A Bridge To Map Users' Social Networking Capabilities To Latent Functions For Product Recommendation. In Particular, We Support Studying Each Users' And Merchandise' Function Representations (Called User Embeddings And Product Embeddings, Respectively) From Records Collected From E-Commerce Web Sites The Use Of Recurrent Neural Networks And Then Observe A Modified Gradient Boosting Bushes Approach

To Transform Customers' Social Networking Functions Into Consumer Embeddings. We Then Increase A Characteristic-Based Matrix Factorization Approach Which Can Leverage The Learnt User Embeddings For Bloodless Begin Product Recommendation.

Our Proposed Framework Is Certainly Powerful In Addressing The Move-Website Online Cold-Begin Product Advice Trouble. We Agree With That Our Look At Can Have Profound Effect On Both Studies And Industry Groups. We Formulate A Unique Trouble Of Recommending Merchandise From An E-Commerce Website To Social Networking Users In "Cold-Begin" Conditions. To The Quality Of Our Understanding, It's Been Hardly Ever Studied Earlier Than. We Advocate To Use The Recurrent Neural Networks For Getting To Know Connected Feature Representations For Each Customers And Products From Data Collected From An E-Trade Website.We Advise A Modified Gradient Boosting Timber Approach To Transform Users' Microblogging Attributes To Dormant Characteristic Illustration Which May Be Easily Included For Product Advice.We Advise And Instantiate A Function-Primarily Based Matrix Factorization Technique Via Incorporating Consumer And Product Capabilities For Cold-Start Product Advice.

CONCLUSION

In This Paper, We've Got Studied A Unique Hassle, Cross Site Coldstart Product Advice, I.E., Recommending Products From Ecommerce Websites To Microblogging Customers Without Historical Buy Facts. Our Essential Idea Is That At The Ecommerce Websites, Users And Merchandise May Be Represented Inside The Identical Dormant Characteristic Area Via Characteristic Getting To Know With The Recurrent Neural Networks. Using A Set Of Linked Users Throughout Both Ecommerce Websites And Social Networking Websites As A Bridge, We Can Study Characteristic Mapping Capabilities Using A Modified Gradient Boosting Bushes Technique, Which Maps Customers' Attributes Extracted From Social Networking Websites Onto Characteristic Representations Discovered From E-Commerce Web Sites. The Mapped Consumer Functions Can Be Effectively Included Into A Chilly-Start Product Recommendation. The Effects Display That Our Proposed Framework Is Certainly Effective In Addressing The Go-Web Site Cold-Start Product Recommendation Trouble. We Agree With That Our Observe Can Have Profound Impact On Each Research And Industry Groups.

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